Artificial Neural Networks

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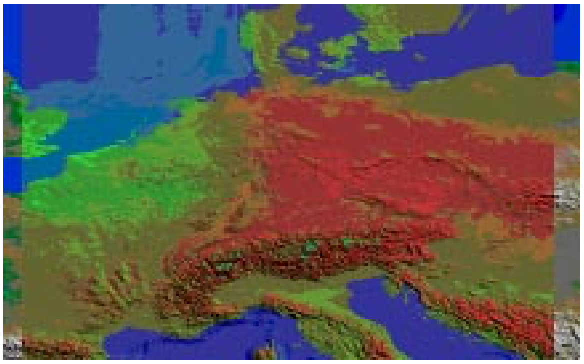
Artificial intelligence is a popular phrase possessing a wide range of definitions. Since the creation of the first computer, designers and users alike have been striving to develop “thinking machines” capable of far more than simply crunching numbers. Artificial neural networks, or ANNs, attempt to follow a biological paradigm to impart “intelligence” to a computer program. A biological neuron is a cell capable of basic computation in that it receives one or more inputs and based on the magnitude of the various inputs and the strength of their connections (synapses), the cell produces an output response. This output response can then be passed as an input to other neurons. The true power of these biological computers comes from the complex interaction of thousands of neurons in a massively parallel architecture.

ANNs are a class of machine learning algorithm capable of establishing relationships between a set of input and a desired output. In its simplest form, an ANN consists of a collection of interconnected nodes representing the neurons, a series of weights that represent the connection strength of input, and an activation function that determines when the weighted sum of inputs is sufficient to trigger an output response. The ANN learns how to map a given set of inputs to a known output value through an iterative training process where the network adjusts the internal weights to minimize output error. Once trained, the ANN provides a functional mapping between inputs and outputs and is then capable of providing output values when given new input values. ANNs represent a class of tool known as universal function approximators, which means they can approximate any function if they are given enough nodes (computing power) and sufficient training data.

Neural networks have been trained to perform a wide variety of tasks including credit checks, speech recognition, and stock market forecasting. We are currently applying ANNs as a highly adaptive nonlinear method for performing spatial interpolation of weather data. For example, many places around the world have long time-series of routine weather observations that could be useful in evaluating historic drought conditions. The spatial distribution of these observing stations is very irregular; typically, weather stations are highly concentrated near heavily populated areas but there are relatively few stations in remote forested areas. The key to examining spatial patterns using these scattered weather observations is the method of spatial interpolation. An ANN has been constructed to spatially interpolate routine daily weather observations using location (latitude and longitude), topography (slope, aspect and elevation), land cover type, and distance to water bodies as inputs for developing spatial interpolation functions that can produce gridded weather data sets at resolutions of 1 to 5 kilometers. We used ANN-derived temperatures to examine the spatial extent of a severe drought episode that occurred during 2003 in Europe. In addition to producing historical spatial weather fields, we are also investigating the application of ANNs to downscaling numerical weather prediction model forecasts. This technique may make it possible to derive a more detailed 1-kilometer resolution weather forecast from a 12-kilometer model output. If successful, this method will cut the time it takes to produce detailed weather information from computer-intensive meteorological models such as MM5. One application would be detailed smoke modeling for individual prescribed fires in near real-time.



Spatial extent of 2003 European drought derived from difference between 2003 and 2001 conditions. Red areas are those hardest hit by drought while green indicates little difference between 2003 and 2001.